1 **Global precipitation estimates from cross-track passive microwave observations using a**

2 **physically-based retrieval scheme.**

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13

14 **Abstract**

15 The estimation of precipitation across the globe from satellite sensors provides a key resource in

16 the observation and understanding of our climate system. Estimates from all pertinent satellite

17 observations are critical in providing the necessary temporal sampling. However, consistency in

18 these estimates from instruments with different frequencies and resolutions is critical. This paper

19 details the physically-based retrieval scheme to estimate precipitation from cross-track (XT)

20 passive microwave (PM) sensors onboard the constellation satellites of the Global Precipitation

21 Measurement (GPM) mission. Here the Goddard PROFiling (GPROF) scheme, a physically-

22 based Bayesian scheme developed for conically-scanning (CS) sensors, is adapted for use with

23 XT-PM sensors. The present XT GPROF scheme utilizes a model-generated database to

24 overcome issues encountered with an observational database as used by the CS scheme. The

25 model database ensures greater consistency across meteorological regimes and surface types by

26 providing a more comprehensive set of precipitation profiles. The database is bias-corrected

27 against the CS database to ensure consistency in the final product. Statistical comparisons over

28 Western Europe and the United States show that the XT GPROF estimates are comparable with

29 those from the CS scheme. Indeed, the XT estimates have higher correlations against surface

30 radar data, while maintaining similar root mean squared errors (RMSE). Latitudinal profiles of

31 precipitation show the XT estimates are generally comparable with the CS estimates although in

32 the southern mid-latitudes the peak precipitation is shifted Equator-wards while over the Arctic

33 large differences are seen between the XT and the CS retrievals.

34

35 **1 Introduction**

36

37 The estimation and mapping of precipitation across the Earth's surface is of great importance.

38 Precipitation (rainfall and snowfall) is fundamental to many aspects of life on Earth, through the

39 provision of fresh water that impacts our economic and social wellbeing. On a scientific level,

40 precipitation plays a fundamental role in linking the Earth's water and energy cycles. To

41 properly understand precipitation within the Earth System, it is necessary to quantify it on a

42 global scale. While rain (and snow) gauges remain the *de facto* source of conventional

43 information on precipitation their uneven distribution, and therefore their representativeness,

44 limits their usefulness for measuring global precipitation. Similarly, surface radar datasets have

45 limited spatial extent. The ability of satellite instrumentation to provide regular global

46 observations is therefore a key component of any global precipitation measurement system.

47

Satellite observations using visible (Vis) and infrared (IR) images from low Earth orbiting (LEO) or geostationary (GEO) satellites provide regular observations of clouds from which estimates of precipitation may be generated. However, although precipitation originates from clouds not all clouds produce precipitation. More importantly, the relationship between the cloud top properties and the precipitation reaching the surface is indirect. Passive microwave (PM) radiometers allow a more direct measure of precipitation to be made since these frequencies are more sensitive to precipitation-sized particles. Multi-frequency PM instruments (e.g. the Special Sensor Microwave Imager Sounder, SSMIS, or the Microwave Humidity Sounder, MHS) allow more complex methods to be used to extract precipitation estimates over a range of different regimes. In 1997 the Tropical Rainfall Measuring Mission (TRMM) was launched, hosting a number of precipitation-related instruments, notably the TRMM Microwave Imager (TMI) and the Precipitation Radar (PR); TRMM finally ended data collection on 8 April 2015. Building upon the success of TRMM, the Global Precipitation Measurement mission (GPM) Core Observatory was launched in 2014, joining a constellation of international satellites equipped with precipitation-capable sensors and providing improved capabilities for the measurement of precipitation from passive and active microwave sensors (Hou et al. 2014).

Alongside the technological development of satellite instrumentation, techniques have been developed and evolved to extract information on precipitation from the satellite observations. Although the Vis/IR observations are relatively indirect, their frequent temporal availability from GEO sensors permits the timely production of near real-time products for applications such as flood forecasting. The more direct observations made by PM sensors have led to a range of precipitation estimates using empirical and/or physically-based schemes. Empirical techniques built upon basic radiometric properties of precipitation, such as the Polarization-Corrected

72 Temperature (Spencer et al. 1986; Kidd 1998) and Scattering Index (Ferraro et al. 1998), have

73 achieved a degree of success (see Kidd et al. 1998). However, while empirically-based schemes

74 are generally simpler and computationally faster, physically-based schemes generally provide

75 more information on precipitation, such as types of hydrometeor and even atmospheric profiles

76 of precipitation. The Goddard PROFiling (GPROF) scheme (Kummerow et al, 2001, 2015) is an

77 example of the latter and has been developed for use with multi-channel microwave observations

78 from conically-scanning (CS) radiometers such as the Special Sensor Microwave/Imager

79 (SSM/I) and the TRMM Microwave Imager (TMI). In the GPM era the constellation of

80 precipitation-capable sensors includes both CS and cross-track (XT) sensors necessitating the

81 incorporation of XT observations into the GPROF scheme.

82

83 This paper describes the adaptation of the GPROF scheme to utilize observations from the XT

84 PM instruments. Section 2 describes the GPROF scheme in detail together with the steps

85 required to adapt it to the observations from the XT sensors, and in particular the incorporation

86 of model information, which is described in Section 3. Initial results from testing of the new

87 GPROF XT scheme using data from the MHS are provided in Section 4, while Section 5

88 provides a discussion of the results and future directions.

89

90 **2 The GPROF retrieval scheme**

91

92 Although the presence of precipitation is often evident in maps of PM brightness temperatures,

93 providing unambiguous retrievals of precipitation is often difficult. This is primarily due to the

94 variability of the surface background, and/or the non-unique observed spectral signatures to

95 hydrometeor profiles/surface rainfall relationships. A greater insight into the radiometric

96   signature may be obtained through inverse radiative transfer modelling, although such techniques

97   are ultimately limited by the model itself and the computational requirements.

98

99   One of the better-known physically-based precipitation retrieval techniques is the GPROF

100   scheme, originally conceived by Kummerow and Giglio (1994). The scheme was devised to not

101   only provide an estimate of the surface precipitation, but also an estimate latent heat release

102   (amongst other parameters) from the vertical structure of the precipitation. In its purest form, the

103   observed brightness temperatures (Tbs) are processed through inverse radiative transfer

104   modelling to provide an estimate of precipitation (see Kummerow et al. 1996; Olson et al. 2007).

105   However, due to the computational expense of such a scheme a Cloud Radiation Model (CRM) -

106   based *a priori* database is employed to provide fully parametric precipitation estimates through a

107   conditional probalistic Bayesian retrieval scheme; critically, once the *a priori* CRM-based

108   database had been established for one sensor, it can be extended to include other passive

109   microwave sensors.

110

111   The basic assumption of the scheme is that the CRM database can accurately describe and

112   represent the precipitation to be retrieved. Early CRM simulations (see Tripoli, 1992; Tao and

113   Simpson, 1993) had relatively simple microphysical schemes that limited not only the

114   representativeness and accuracy of the results, but also proved to be computationally expensive.

115   Similarly, the matching of the satellite observations to the CRM database was (at the time) time-

116   consuming, consequently a rain/no-rain screen was introduced in the earlier versions of GPROF

117   so that the database was only accessed for observations likely to have rain. The CRM database

118   was then interrogated to find a profile that best matches the spectral signature of the satellite

119 observation. However, no distinct precipitation signatures may exist since the observed radiances

120 are affected by a range of factors other than precipitation, including surface effects, radiometric

121 noise, together with beam filling effects resulting from the (relatively) large footprints, etc.

122 Furthermore, since PM sensors have a limited number of channels and thus cannot uniquely

123 identify all the possible radiometric signatures, the accuracy of the retrieval is based upon the

124 ability of the observations to resolve the true spectral signature (Smith et al. 1994). While it is

125 possible to select the database entry with the closest signature, the retrieved value can only be an

126 approximation of the true value. A Bayesian scheme is therefore used to generate not only an

127 estimate of precipitation, but also an estimate of uncertainty of the retrieval itself (see Elsaesser

128 and Kummerow 2015).

129

130 The GPROF retrieval scheme has undergone a number of modifications over time to improve the

131 retrievals, including improvements to the radiative transfer model used in the generation of the *a*

132 *priori* database, freezing level heights over the oceans, discrimination of regions of stratiform vs

133 convective precipitation, cold surface screening, etc. (see Kummerow et al. 2001). The current

134 GPROF scheme implemented for the CS radiometer observations, known as GPROF2014, is

135 described in Kummerow et al. (2015). To better define the range of suitable hydrometeor profiles

136 in the *a priori* database, together with improving the computational efficiency the current CS-

137 GPROF scheme, the database incorporates model-derived measures of skin temperature (Ts) and

138 total precipitable water (TPW). The categorization of the profiles by Ts and TPW is based upon

139 the findings of Berg et al. (2006) to account for regional differences in the relationship between

140 surface precipitation and satellite radiances. Furthermore, since the background surfaces are

141 deemed to be influential on the spectral signature of the observed Tbs, separate databases are

142   generated for 15 different surface types, including land, ocean, ice, etc. The profiles included in

143   each of these databases are based upon the satellite observed radiances with rain rates derived

144   from co-located surface-based radar or satellite-based radar (i.e. CloudSat Cloud Profiling Radar,

145   CPR, and/or the TRMM Precipitation Radar, PR). In the retrieval process, model-generated Ts,

146   TPW and surface type are attached to each set of observed brightness temperatures: the surface

147   type selects the appropriate database and the Ts and TPW identifies which set of profiles within

148   the database to use for the retrieval.

149

150   Thus, the GPROF scheme comprises of three main processing steps as identified in Figure 1. The

151   first involves the generation of the *a priori* database that contains radiances with associated

152   surface rainfall, hydrometeor profiles and other pertinent data. The second step preprocesses the

153   satellite observations by attaching the surface types and model-derived Ts and TPW to the set of

154   brightness temperatures for each satellite footprint. The final stage performs the Bayesian

155   retrieval of the precipitation by comparing the satellite observations to the radiances in the

156   appropriate database with the same Ts and TPW.

157

158   2.1 Adaption of GPROF to the XT sensors

159   The inclusion of the XT sensors within the GPROF scheme is of great importance; first, it

160   doubles the number of current PM sensors available for precipitation estimation and second, it

161   provides a consistent approach to the retrieval of precipitation from the passive microwave

162   radiometers that are part of the GPM constellation (see Table 1). The main differences between

163   the CS and XT instruments are primarily the scanning geometry and channel selection. CS

164   radiometers provide a (nearly) constant Earth Incidence Angle (EIA) and therefore consistent

footprint resolution (at each frequency) and polarization across the swath of the sensor. However, XT instruments scan perpendicular to the satellite's trajectory such that the center of scan is close to, or at the sub-satellite point. Observations are taken at equal scan angles across the satellite swath resulting in a changing EIA with each scan position and consequently the size of each footprint increases away from the nadir point, together with changes in the polarization and the length of the atmospheric path between the Earth's surface to the sensor. In addition, CS radiometers have traditionally used (imaging) channel frequencies typically between about 6.9 and 90 GHz, while XT sensors have utilized higher (sounding) frequencies up to about 190 GHz. However, newer CS instruments including the Special Sensor Microwave Imager Sounder (SSMIS) and the GPM Microwave Imager (GMI) also incorporate these higher frequencies.

Although most precipitation retrieval schemes have concentrated the observations from CS instruments (see Kidd and Huffman 2011; Kidd and Levizzani 2011), a number of techniques have been developed to exploit the observations from XT sensors. These include neural network approaches by Surussavadee and Staelin (2008) and Sano et al. (2015), the 183-WSL technique of Laviola et al. (2013) and a technique using canonical analysis by Casella et al. (2015). Of particular interest in the context of this paper is the Microwave Integrated Retrieval System (MiRS, Iturbide-Sanchez et al. 2011; Boukabara et al. 2011) that is used to generate a number of geophysical parameters from both CS and XT passive microwave observations using an iterative physical inversion scheme, although only the NOAA-18 and MetOp-A XT MHS sensors are used for precipitation estimation. However, current schemes only provide XT-only or CS-only retrievals of precipitation. The GPROF scheme described in this paper is adapted so that the

187 retrievals from both the CS and XT sensors can be obtained through the same methodological

188 framework.

189

190 The development of the XT-GPROF scheme has been based upon the MHS instrument, but

191 recently extended to other XT sensors. The MHS has XT scan angles that vary from +49.44° to -

192 49.44° resulting in an EIA ranging from -58° to +58° and resolutions varying from 15.88×15.88

193 km at nadir to 27.10×52.83 km at the swath edge (along-track $\times$ cross-track). In addition, the

194 polarization changes from primarily vertical to primarily horizontal (or vice versa depending on

195 the channel), and the atmospheric path increases to 1.88x that of the nadir path at swath edge.

196 Although the details for each XT sensor are similar, they have subtle differences due to scan

197 angles, frequencies used and nominal sensor resolution. The consequences of the variable EIA

198 were therefore explored in the prototype XT GPROF scheme and are outlined below.

199

200 2.2 Prototype XT-GPROF scheme

201 In preparation for the operational version of the XT-GPROF scheme a prototype scheme was

202 devised and tested; this prototype version augmented the CS-GPROF scheme with features that

203 were deemed to be useful for the XT-GPROF version. As noted above, the changing EIA of the

204 XT sensors impacts the resolution, polarization and atmospheric path of the observations. It was

205 therefore assumed that observations at each scan position would need to be considered

206 separately, or at least in groups of alike scan positions. An initial comparison of the impact of

207 polarization with scan position upon the retrievals revealed only small differences, consequently

208 the variation in the polarization with scan position was not considered at this stage. The effect of

209 the resolution of the observations was also investigated. Rather than provide databases for each

9

210   of the 90 scan positions, databases were generated for 5 similar EIA scan position bins. Since the

211   CS-GPROF scheme already comprises of 15 databases (one for each surface type), this meant

212   that the prototype XT scheme required a total of 75 databases (15 surfaces x 5 scan position

213   bins).

214

215   The databases generated for the prototype version of the scheme were generated from matchups

216   between the MHS satellite observations matched with collocated surface or satellite radar

217   measurements, similar to that of the CS-GPROF scheme. Although this methodology worked

218   well for the CS-GPROF databases, the number of available MHS-surface/satellite radar

219   matchups was more limited for the XT databases. In addition, a greater number of databases (due

220   to incorporating scan-positions) reduces the sample-size in each database resulting in increased

221   noise and potentially missing retrievals. Since the MHS-channel frequencies are less sensitive to

222   the surface background it was decided produce a single, surface-blind database that relied solely

223   upon the modeled Tbs to adequately resolve the precipitation over any surface and for any scan

224   position. Furthermore, to ensure an adequate number of database entries, the database was

225   populated with profiles from the Multi-scale Modeling Frameworks (MMF) v2.1 model (as

226   described in section 3).

227

228   2.3 The XT-GPROF scheme

229   The characteristics of the current operational XT-GPROF scheme, together with those of the CS-

230   GPROF scheme, are summarized in Table 2. The key difference between the two schemes is that

231   the XT version uses a single model-derived database as opposed to the observation-derived

232   databases of the CS-version. To ensure consistency between the CS and XT databases the mean

233   rainrate per XT database bin is bias-corrected against the CS databases to ensure comparable

234   retrievals. In addition, the XT scheme incorporates a simple empirically-derived scan position

235   adjustment that mitigates the effects of the changing resolution and beam filling upon the

236   precipitation retrievals. This correction is designed to ensure that the precipitation retrieved at all

237   scan angles is comparable with the nadir-only calculations from the MMF model. Also of note,

238   unlike the diagnostic identification of frozen precipitation (i.e. snow) in the CS-GPROF scheme,

239   falling snow is quantified directly from the XT retrieval itself.

240

241   Crucial to the success of the XT-GPROF retrieval scheme is the MMF model. The primary

242   purpose of using the MMF-simulated database is to establish a quality-controlled and physically-

243   based precipitation retrieval algorithm consistent with the GPM core satellite as well as the GPM

244   constellation satellites. The advantage of using a MMF-simulated database includes i) the

245   simulated microwave Tbs are derived from the identical physical assumptions and calculation

246   methods; ii) it is straightforward to generate a Tb database for all constellation satellite sensors,

247   iii) the database quality can be readily tracked for further improvement, and iv) the database can

248   include drizzle and snowfall signals that might be missed through the use of an observation-

249   derived database. Critically the MMF provides physically consistent surface and environmental

250   parameters together with associated radiances necessary to generate the XT database.

251

252   **3 The MMF model-derived database**

253

254   3.1 The MMF model

255 The NASA MMF model is composed of the Goddard Earth Observatory System V4 (GEOS4)

256 and the Goddard Cumulus Ensemble (GCE) model. The GCE utilizes the new Goddard 4ICE

257 microphysics, which includes explicit hail categories and many improved microphysics

258 parameterizations (Lang et al. 2014, Chern et al. 2015). GEOS4 simulates general circulations

259 and surface flux with a climate-scale grid configuration ($2.5° \times 2.0°$ horizontal grid spacing),

260 which forces fine-resolution two-dimensional GCE models with a cloud-resolving-scale grid

261 configuration (4 km horizontal grid spacing). The GCE explicitly simulates cloud dynamics and

262 microphysics processes every 10 seconds, and the mean profiles of the GCE meteorological

263 fields and hydrometeors feed back to the GEOS4 grid every hour. For computational efficiency,

264 the GCE is configured in a two-dimensional (2D) grid (64×1 horizontal and 41 vertical) using a

265 cycling boundary condition. In this way, numerous copies of explicit cloud-resolving model

266 simulations replace ill-posed parameterization of sub-grid convection and cloud processes in

267 GEOS4. This hybrid structure of the climate model enables a more realistic representation of

268 convection without using ill-posed convective parameterization, improving many cloud-related

269 features, such as the diurnal cycle of precipitation (Tao et al. 2009), land-atmosphere interactions

270 (Mohr et al. 2012), and distributions of ice water content (Chern et al. 2015).

271

272 Another advantage of using the MMF is that the spatial scale of MMF-simulated cloud-

273 precipitation parameters is close to those of satellite observations. While a traditional climate

274 model often assumes complex sub-grid distributions or overlapping patterns for evaluation

275 against satellite data (Webb et al. 2001), the MMF explicitly simulates the physical structure of

276 cloud and convective processes through the 2D GCE; thus, the satellite instrumental simulator

277 can be applied straightforwardly. The precipitation and microphysics parameters of the MMF

278   simulations can be evaluated directly against the satellite measurements (Matsui et al. 2009); if

279   these synthetic satellite observations are in reasonable agreement with specific satellite

280   measurements, a set of MMF-simulated satellite signatures and geophysical parameters may be

281   used to populate databases for similar satellite sensors (Matsui et al. 2013).

282

283   The drawback of using a MMF-simulated database is associated with the intrinsic nature of

284   biases within models, including i) MMF dynamics and microphysics process and ii) forward

285   model assumptions. These problems, especially the MMF biases, have been significantly reduced

286   through various observation and model improvements, and are briefly summarized below:

287   • *Microphysics*. A new Goddard 4ICE microphysics scheme replaced the original Goddard

288   3ICE microphysics (Lang et al. 2014, Chern et al. 2015). This new scheme predicts an

289   explicit hail category in addition to existing hydrometeor categories (cloud, rain, ice

290   crystals, snow aggregate, and graupel). The occurrence of hail in convective cores is

291   relatively rare and its spatial coverage is also very small (less than a few percent), but it

292   improves the representation of strong precipitation intensity and the strong depression of

293   microwave Tbs associated with convective core structure.

294   • *Vertical levels*. The original GCE vertical resolution contained 28 levels up to the

295   tropopause. However, it was found that Rayleigh dampening in the upper model layers

296   tends to suppress vertical velocity of deep convection (maxima: ~10 m s^{-1}). Thus, the

297   number of vertical levels were increased to 41 so that deep convection could be allowed

298   to overshoot the tropopause, unaffected by Rayleigh dampening. As a result the

299   maximum vertical velocity has been increased significantly (maxima ~30 m s^{-1}),

300   improving the representation of echo-top height distributions.

301   • *Background meteorology*. The free-running mode of long-term MMF (and any climate

302   model) simulations often causes internal climate drift due to biases in the physics

303   schemes and their interactions. For the production of the database, the background

304   meteorology should be as close as possible to the observation. Consequently, the mean

305   meteorological fields of the MMF simulation were nudged using the European Centre for

306   Medium Range Weather Forecasts (ECMWF) Interim re-analysis (ERA-Interim)

307   reanalysis. This suppresses the overestimation of high precipitation in the tropical warm

308   pool region which are associated with frequent shallow convection in previous MMF

309   simulations (Tao et al. 2009).

310

311   3.2 The RT model

312   The forward model used in the database generation is the GPM simulator suite of the Goddard

313   Satellite Data Simulator Unit (G-SDSU, Matsui et al. 2013). Microwave brightness temperatures

314   (Tb) are computed through a two-stream model with Eddington's Second Approximation

315   (Kummerow 1993) along satellite FOV-slant paths (Olson et al. 2001). Land-surface emissivity is

316   estimated from the satellite-estimated climatology map (Aires et al. 2011), while water-surface

317   emissivity is based on an empirical parameterization as a function of salinity, wind speed, and

318   temperature (Wilheit 1979). Note that surface emissivity and skin temperature are assumed

319   homogeneous in the forward model and for each copy of the 2D GCE. Gaussian weighting

320   functions of brightness temperatures are then used to generate the satellite-resolution Tbs in

321   combination of specific beam widths of sensors, sensor viewing angle, satellite altitude, and local

322   elevation.

323

324 Hydrometeor single-scattering properties are computed at each GCE grid cell via the Lorenz-Mie

325 method with effective refractive indices through the Maxwell-Garnett mixture method. Single-

326 scattering calculation follows the exact assumptions of Goddard 4ICE microphysics for size

327 distributions and bulk effective density, including new empirical snow-graupel size and density

328 mapping (Lang et al. 2014). Single-scattering properties are integrated over the two liquid and

329 four ice categories to represent bulk single-scattering properties.

330

331 3.3 Implementation

332 The XT-GPROF scheme therefore currently relies on a single database (covering all surface

333 types) which is derived from the MMF model. The MMF simulations were generated for 1 year

334 from 1 January 2007 to 31 December 2007 with profiles sampled over the globe equidistantly

335 every c. 200 km; large-scale meteorological conditions (temperature and humidity profiles) were

336 nudged using the ERA-Interim every 24 h in order to avoid internal climate drift.

337

338 As noted above, to ensure consistency between the CS and XT retrievals the XT database is bias-

339 corrected against the CS database. Figure 2 depicts the mean rain rate per database bin for the

340 aggregated GMI databases and the MMF-derived database for the MHS sensor. While the

341 general form of the databases are broadly similar, it can be seen that the MMF-derived database

342 provides profiles over a greater range of Ts and TPW than the GMI database; the MMF-derived

343 database ranges from 189-344 K for Ts and 0-95 g Kg^{-1} for TPW compared with the GMI

344 database ranging from 230-337 K for Ts and 0-80 g Kg^{-1} for TPW. While both schemes use Ts

345 and TPW derived from the ECMWF model, the key difference is the restriction imposed by

346 sampling on the GMI observational database. One of the consequences of the CS database being

15

347 based upon observations is that the retrieval will fail if it attempts to retrieve a profile beyond

348 any previously seen meteorological condition. While the distribution of the mean rain rates is

349 similar between the two databases, the greater range of the MMF database provides higher rain

350 rate profile entries for high values of TPW.

351

352 The MMF-derived databases initially developed to generate products from the MHS sensor

353 (Kidd 2014a-d) are currently being extended to include the Advanced Technology Microwave

354 Sounder (ATMS) on the US Suomi National Polar-orbiting Partnership (NPP) satellite and the

355 Sondeur Atmosphérique du Profil d'Humidité Intertropicale par Radiométrie (SAPHIR) on the

356 French/Indian Megha-Tropiques satellite.

357

358 **4. Verification and validation**

359

360 The XT-GPROF retrievals are generated in near real time by the GPM Precipitation Processing

361 System (PPS) at NASA's Goddard Space Flight Center. The XT v1-2 retrievals (Kidd 2014a-d)

362 for the MHS and CS v1-4 retrievals (Kummerow 2014a-e) for the AMSR2, GMI and SSMIS are

363 used in this study. The spatial resolution of the CS-GPROF retrievals are set by the size of the

364 size of each sensor's 3 dBZ sensitivity at 37 GHz; this equates to a retrieval resolution of 12×7

365 km for AMSR2, 14×8.6 km for GMI and 44.2×27.5 km for SSMIS. The scan position

366 corrected XT retrievals are deemed to be comparable with the nadir-only 15.88×15.88 km

367 resolution of the model-generated database, regardless of scan position. In addition, comparisons

368 were also made for the SSMIS using a resolution of 15×15 km to permit more consistent

369 comparisons with those from the other sensors.

370

Surface radar data over two regions, the United States, and Western Europe, was used as ground

'truth'; both these regions have extensive, high-quality radar coverage suitable for the validation

of satellite products (see Kidd et al. 2012; Ebert et al. 2007). However, due the spatial and

temporal sampling of the radar data over these regions two different approaches were adopted for

the satellite/surface comparison. Over the United States radar data is available at a spatial

resolution of $0.01° \times 0.01°$ every 2 minutes from the National Oceanic and Atmospheric

Administration (NOAA) National Severe Storms Laboratory (NSSL) Multi-Radar/Multi-Sensor

(MRMS) system (Kirstetter et al. 2012). The satellite estimates were subsetted from the orbital

files for each two minute segment; the time stamp was set to the end time to match the timestamp

of the corresponding radar data. The satellite footprints were then mapped to the radar data grid

for each two minute segment and the radar data averaged within the satellite footprint to provide

a corresponding surface rainfall value. For this comparison, only radar data with the highest

quality index (see Kirstetter et al. 2012) equal to 1.0 over the entire footprint were included in

the analysis. Furthermore, data west of 100°W were excluded in the analysis due to the paucity

of radar coverage over the mountainous western United States.

386

Radar data over Western Europe (Met Office 2003) was obtained from the Centre for

Environmental Data Archive (CEDA). The data are a composite of radars covering the United

Kingdom, France, Germany and the Netherlands, mapped to an equal area projection at 5×5 km

spatial resolution every 15 minutes. Due to the coarser resolution of the radar data, matching the

surface radar to satellite footprints necessitates a different matching approach. The centers of

each satellite footprint were mapped to the 5×5 km radar data; where the radar data was fully

393   within the satellite footprint a weight of 1.0 was assigned, otherwise a weight less than one was

394   assigned on the margins of the satellite footprint based upon the fraction coverage of the satellite

395   footprint. Since no radar quality index was available for the European radar data, a skill-score

396   map derived from previous satellite/radar comparison (see Kidd and Hou 2012) was used to

397   provide a measure of quality.

398

399   *Precipitation retrieval by intensity:*

400   One of the artifacts associated with the Bayesian retrieval scheme is that if any profile within the

401   searched set of profiles within the database contains any precipitation, all retrievals using that bin

402   will return a non-zero precipitation result leading to an exaggerated occurrence of precipitation.

403   Figure 3 shows the satellite/surface-radar ratio of the accumulated (liquid-only) precipitation in

404   0.01 mm h^{-1} bins for 6 March 2014 to 5 March 2015 over the US. The retrievals from all the

405   sensors exhibit significant over estimation at low rainfall intensities: in particular, the AMSR2

406   retrievals show nearly a 50-fold overestimation of precipitation accumulation in the lowest

407   (>0.00-0.01 mm h^{-1}) bin, while the MHS show a more modest 8-fold overestimation. However, it

408   should be noted that these very low-intensity comparisons are somewhat dubious due to the

409   statistical nature of the retrieval and the sensitivity of the surface radar dataset to very light

410   precipitation. Nevertheless, Figure 3 shows that the overestimation of light precipitation is

411   matched by an underestimation of the moderate intensities for the AMSR2, GMI and MHS

412   retrievals; the SSMIS underestimates the precipitation accumulation (about x0.7) across all

413   intensities above 0.25 mm h^{-1}. Although some of this underestimation by the SSMIS could be

414   attributed to the large retrieval footprint (44.2 x 27.5 km), it would be expected that this would

415   be compensated by overestimation at other rain intensities.

416

417   Since all the retrievals overestimate the very light precipitation, it is therefore advisable to

418   threshold the rain/no-rain boundary at about 0.1 mm h^{-1}, although differences occur in the

419   threshold between the sensors and over different regions. The ideal rain/no-rain threshold may be

420   found by adjusting the rain rate threshold of the satellite retrieval so that the rain and no-rain

421   occurrences match those of the surface radar; Figure 4 maps these thresholds over the US for the

422   retrievals from each of the four sensors. The SSMIS generally exhibits the lowest rain/no-rain

423   thresholds generally below 0.2 mm h^{-1}, while the MHS shows the highest rain/no-rain threshold

424   at about 0.2 mm h^{-1} over land, but higher over the coastal oceans; these higher thresholds

425   indicate that the satellite estimates are overestimating the occurrence of precipitation in these

426   regions. However, all show similar patterns in the distribution of the threshold, with generally

427   higher values over the Mississippi valley, and lower values over the mountainous Western US,

428   and along the Appalachians in the East. The variations in the distribution of the thresholds

429   suggest a regional effect on the surface reference data (under/over estimation by the surface

430   radar) or a surface background effect.

431

432   *Statistical performance*

433   Two basic statistical measures were used to assess the performance of the retrievals over

434   Western Europe and the US, namely the correlation coefficient and root mean squared error

435   (RMSE). The comparisons were performed on instantaneous retrievals using only high-quality

436   radar data for each day between 6 March 2014 and 5 March 2015. A rain/no-rain threshold of 0.1

437   mm h^{-1} was set for both the satellite retrievals and the radar estimates (values less than 0.1 mm h^{-}

438   ^{1} being set to zero). In addition, for the summary of daily statistical performance, only days on

439   which more than 1% of the radar data was raining were included in the analysis. Figure 5 shows

440   the occurrence of the number of days which attained correlations within the respective

441   correlation bins. At the native retrieval resolutions the SSMIS (44.2 × 27.5 km) performs best

442   with more than 80% of the days having correlations of 0.6 and above; the MHS in comparison

443   has about 45% of the days with correlations above 0.6. However, the large footprint of the

444   SSMIS (based upon the resolution of the 37 GHz frequency channel) means that precipitation

445   features are smoothed compared with retrievals with a higher-spatial resolution; consequently the

446   correlations will be higher for the same precipitation events. If the SSMIS retrievals are

447   compared with collocated radar sampled at 15 ×15 km (comparable with the other retrievals), the

448   occurrence of correlations above 0.6 drops to less than 20%, less than those of the AMSR2, GMI

449   or MHS. Performance of the retrievals for the RMSE shows a similar grouping: the higher

450   resolution retrievals show a broad peak from about 0.4-0.6 to 1.2-1.4 mm h^{-1}, while the SSMIS

451   has a more distinctive peak at 0.6-0.8 mm h^{-1}. However, if the SSMIS is compared at the higher

452   resolution, the distribution of RMSE is similar to the other retrievals although with a higher

453   occurrence in the lowest, 0.0-0.2 mm h^{-1} bin.

454

455   Over Western Europe the distribution of daily correlations has a greater range; over the US the

456   correlations were concentrated between 0.3 and 0.8, over Europe correlations lie generally

457   between 0.0 and 0.8, as shown in Figure 6. It can be seen that the performance of all the

458   retrievals is relatively consistent with the MHS retrievals performing slightly better as noted by

459   the higher occurrence of correlations in the 0.6-0.7 category. Interestingly, despite the larger

460   footprint of the SSMIS, the retrievals are not significantly better than the higher-resolution

461   retrievals (as was the case of the United States), and that the correlations are broadly similar

462   when the higher-resolution SSMIS retrievals are considered. Analysis of the RMSE scores show

463   a similar performance between the different retrievals at the finer resolutions with peak RMSEs

464   between 0.2-0.4 and 0.4-0.6 mm h^{-1}; the coarser native-resolution SSMIS retrieval having

465   slightly lower (better) RMSE. The differences in statistical performance between the US and

466   Europe are most likely a combination of different climate regimes and the relative quality of

467   surface radar data.

468

469   The effectiveness of the XT scan-position correction on the retrieved precipitation is assessed

470   through a comparison over the US between the edge-of-scan and near-nadir estimates. Scan

471   positions 1-22 and 69-90 were assigned as edge-of-scan, while 23-68 as near-nadir. As Figure 7

472   shows, the differences in the correlation coefficient between these retrieval groups is small, with

473   the edge-of-scan retrievals providing slightly better correlations than those near-nadir. We can

474   therefore assume that the retrievals have comparable validity irrespective of scan position.

475

476   To assess the spatial variability of the correlation between the satellite and surface estimates,

477   correlations were calculated between all instantaneous satellite/surface collocated matchups on a

478    $1° \times 1°$ grid for the period 6 March 2014 through 5 March 2015 over the US. The maps of the

479   these correlations are plotted in Figure 8 for the four satellite products at their native retrieval

480   resolution, together with those of the SSMIS at 15×15 km resolution. The paucity of radar

481   coverage over the western half of the US is clearly visible with correlations typically less than

482   0.50. Over the eastern half of the US correlations are generally better than 0.60, with the SSMIS

483   producing correlations over 0.70. However, if the SSMIS retrievals are compared at the 15×15

484   km resolution, these correlations drop to between about 0.60 and 0.65, similar to those of the

485   other products.

486

487   *Annual global estimates*

488   Despite the comparable statistics performance of the XT retrievals with those of the CS over the

489   US and Western Europe, a key issue is whether these estimates provide reasonable global

490   estimates. The mean annual precipitation for all four sensor types has been calculated (for all

491   data $\geq$ 0.0 mm h^{-1}) for the period 6 March 2014 through 5 March 2015 (the first year of GMI

492   data availability) with the results shown in Figure 9. The CS retrievals produce similar estimates

493   with all the main regional-scale features evident; the XT retrievals also show these features

494   although subtle differences exist. The XT retrievals along the Inter-Tropical Convergence Zone

495   (ITCZ) are generally slightly less than those of the CS retrievals with some regional variations,

496   such as off the West coast of Africa. Precipitation in the mid-latitudes is broadly similar,

497   although differences can be noted along the South Pacific convergence zone and along the storm

498   tracks of the Southern Oceans. The AMSR2 and SSMIS estimates produce significant

499   precipitation over the polar regions (the GMI only observes up to 68° N/S) with retrievals from

500   the SSMIS producing mean daily precipitation of 3 mm d^{-1} (water equivalent), while the AMSR2

501   retrievals produce nearly 2 mm d^{-1}. Breaking the annual totals down into the occurrence of

502   precipitation by intensity (see Figure 10) shows that the high latitudes exhibit the greatest

503   differences between the retrievals with the MHS showing the least occurrence of precipitation

504   over land and ocean across all intensities, although note the limited extent of the GMI data. At

505   the mid-latitudes (60°-30°S and 30°-60°N) all the techniques have similar occurrences of

506   precipitation intensity for land and for ocean, although the GMI generates more high-intensity

507   precipitation. Within the Tropics (30°S-30°N) there appears to be more variation between the

508   techniques and background surfaces: over the ocean the GMI and AMSR2 produce less light

509   precipitation than the SSMIS and MHS retrievals, while over land the retrievals are similar for

510   light precipitation. However, for higher rain intensities the GMI and AMSR2 have a higher

511   occurrence of precipitation than the SSMIS and MHS retrievals.

512

513   Latitudinal profiles of mean daily rainfall are shown in Figure 11; the differences between the

514   XT MHS retrievals and those of the CS retrievals are evident, particularly above 70°N and south

515   of 30°S. Further analysis shows that above 70°N the CS retrievals are affected by melting snow

516   and ice at the surface during the Arctic summer. South of 20°S, the XT retrievals show a peak in

517   precipitation at about 35°S, north of that suggested by the CS retrievals. However, at higher

518   southern latitudes the XT estimates are closer to those from the GPM Dual-frequency

519   Precipitation Radar (DPR) than the CS estimates. Outside these regions the agreement is

520   generally good, although the peak precipitation produced by the MHS at about 5°N is about 10%

521   less than that of the CS sensors, but similar to that obtained by the DPR.

522

523   **5. Discussion and Conclusion**

524

525   Although the basic premise of the GPROF retrieval scheme is relatively simple, the

526   implementation of the scheme is less straight forward, particularly so with the XT sensors.

527   Overall the XT scheme aims to provide retrievals that are comparable with those of the CS

528   retrievals to ensure a homogenous dataset, however fundamental differences between the sensor

529   types necessitates variations in the retrieval scheme. The most notable differences between the

530 current schemes relate to the database itself. The choice of the MMF-modeled database rather

531 than the observational database of the CS is primarily due to the representativeness of the

532 database entries: Preliminary tests using a XT observational database produced too many

533 'missing' retrievals. In addition, the use of different data sources to generate an observational

534 database potentially contributes additional noise within the database itself as well as potential

535 inconsistencies between the different regimes used in the database creation. While the model

536 itself is not perfect, one advantage of the modelled database is the consistency across the

537 different profile entries: an increase in TPW or Ts leads to a corresponding and predictable

538 change in the profile entry.

539

540 Statistical comparisons between the satellite retrievals and the surface radar data show that the

541 model-based XT MHS retrievals are at least comparable with those of the observational-based

542 CS retrievals. While the SSMIS retrievals outperform other estimates at its native retrieval

543 resolution, the statistical performance of the SSMIS retrievals is much reduced when compared

544 at a similar scale to the other retrievals. For similar spatial resolutions, the MHS retrievals

545 exhibit generally higher correlations than the CS retrievals. Despite the MHS retrievals

546 performing well statistically, some issues remain. As noted in Figures 3 and 4, the rain/no-

547 threshold for the MHS retrievals is higher than those for the CS retrievals, particularly so over

548 the coastal-ocean region.

549

550 In terms of the global distribution of mean annual precipitation (Figure 9) two principle regions

551 can be identified where substantial differences occur between the XT and CS retrievals. The first

552 is over the high latitude regions in the northern hemisphere where the CS retrievals (AMSR2 and

553   SSMIS) produce much more precipitation (c. 1.8 and c. 2.9 mm d^{-1} respectively) than the XT

554   MHS retrieval (0.2 mm d^{-1}). Although the MHS value appears low, the MHS results presented

555   here are similar to the 2009-11 climatology provided by the MiRSv4.0 product in Boukabara et

556   al. (2011); the AMSR2 and SSMIS values are certainly too high. Closer analysis of the data

557   found that the majority of the precipitation generated by the AMSR2 and SSMIS retrievals was

558   associated with the summertime melting of the snow and sea ice over the Arctic. The second

559   region where discrepancies between the XT and CS retrievals are evident over the southern

560   oceans, and in particular over the South Pacific Ocean around 30°S between 150°W and 120°W;

561   here the MHS produces a maxima in the order of about 8 mm d^{-1} whereas the CS retrievals show

562   a less clearly defined maxima of about 6 mm d^{-1} to the northwest. These differences are also

563   evident in the latitudinal profiles shown in Figure 11, which also highlights the widespread

564   differences between the XT and CS estimates over the southern hemisphere south of 30°S. If the

565   estimates from the DPR are included it can be seen that although the MHS retrievals are too high

566   around 35°S, the CS estimates are between 2 and 4 times that of the DPR or MHS estimates by

567   60°S. These differences require further investigation but probably arise from a combination of

568   physical reasons and retrieval assumptions. For example, over the oceans the XT and CS use

569   different combinations of channel frequencies, the XT using channel frequencies above 89 GHz

570   while the CS sensors use primarily frequencies below 89 GHz, therefore the fundamental

571   observation-rainfall relationships will be different. In addition, the observational database used

572   by the CS retrievals make certain assumptions in the higher-latitude regions based upon the

573   matchups between the TRMM PR and satellite observations in the Tropics. Some of these

574   differences might also be addressed through improved representation within the databases (in

575   both/either the XT and/or CS), or a more fundamental way the database is devised. For example,

576 databases are currently organized into bins of TPW and Ts (to be replaced by TPW and T2m in

577 version 2), but since the XT sensors are less sensitive to the surface than the CS sensors due to

578 their channel selection, the use of the Ts or T2m might be less useful or inappropriate for

579 constraining the XT retrievals.

580

581 Both the observation-based CS-GPROF and model-based XT-GPROF schemes rely upon an *a*

582 *priori* database for the physically-based precipitation retrieval within a Bayesian framework.

583 However due to unique hybrid structure of traditional climate model and cloud-resolving models,

584 the MMF provides more complete distributions of various types of precipitation and associated

585 microwave Tb in sampling space. This approach is also beneficial for generating databases for

586 various microwave instruments of GPM constellation partners, since it simply relies on the

587 unified framework in terms of the cloud-precipitation model and the GPM forward model. On

588 the other hand, retrieval errors and uncertainties depend on the quality of the MMF simulations

589 and a forward model.

590

591 In the present study, the NASA MMF runs a 2D GCE with 4 km horizontal grid spacing and 41

592 vertical levels that is appropriate for resolving deep and organized convection. While it may not

593 be suitable for numerically representing less-organized convection on a scale of less than 10-grid

594 spacing of the GCE, the 4 km GCE horizontal grid spacing may effectively resolve cloud

595 dynamics on the size of 40 km or larger. Even in the 3D grid framework with 1 km grid spacing,

596 the GCE simulation does not necessarily represent the structure of isolated convection well

597 (Matsui et al. 2009). For such intermediate-size convection, a grid size of at least 250 m is

598 required for the realistic simulation of a precipitation system (Lang et al. 2014). The 2D grid

26

599 structure with homogeneous surface conditions also biases the updraft structure, cloud dynamics,

600 and precipitation intensity and types in contrasting regions, such as between continental and

601 ocean environments (Matsui et al. 2015). This may require heterogeneous surface patch (either

602 land-cover types or land-ocean mask) in GCE to induce the necessary mesoscale pressure

603 gradient to invigorate continental / island convection (Robinson et al. 2011). This sub-grid

604 thermal patch may also create more realistic precipitation Tb signals on coastlines, where passive

605 microwave retrievals typically have biases due to rapid gradient of the surface emissivity (Kidd

606 1998).

607

608 In future versions of the XT database, it is planned to relax these issues through conducting

609 MMF simulations with finer-resolution GCE (250 m horizontal grid spacing) over sub-grid

610 heterogeneous surface conditions. Importantly these new MMF simulations, with new physics

611 and grid configurations, will be constrained against the GPM combined product (GPM-2BCMB),

612 in terms of precipitation intensity, microphysics, and storm structure. In parallel, the MMF

613 simulation will be evaluated against the GMI Tbs and DPR reflectivities statistics through the

614 GPM simulator. Although the new MMF update could take significantly more computational

615 time and effort, Matsui et al. (2015) established a convective- and microphysics quasi-

616 equilibrium concept based on the time-invariant statistics of satellite observations over the entire

617 Tropics. This concept suggests that single day statistics of microphysics and convection are

618 similar to the climatology, as long as they are combined over the entire Tropics. This provides

619 more rapid MMF development cycle; e.g., global statistics from single-day MMF simulation can

620 be evaluated and constrained toward climatology statistics derived from the TRMM and GPM

621 satellites.

622

627

Appendix. MMF-GPROF database improvement.

629

Figure A1a shows the improvement of the MMF-simulated microphysics characteristics of deep convective clouds (echo-top height > 7 km) in the forms of the TRMM Precipitation Radar (PR) Contoured Frequency of Altitude Diagram (CFAD). TRMM PR CFAD shows dramatic transition of reflectivity distributions. There are distinct three transitional zones: solid-phase zone (i.e., above 8km) where the presence of solid precipitation particles generated narrow and vertically constant reflectivity profiles, mixed-phase zone (i.e., between 5 and 8 km) where the aggregation and melting process of frozen particles dramatically increased reflectivity distributions, and liquid-phase zone (i.e., below 5 km) where liquid raindrops dominate the radar backscattering signals.

639

The CFAD from the MMF V1 database depart from characteristics of observed CFAD; e.g., maximum echo-top height is below 14km (lacking the undiluted hot tower), not distinct spectral broadening in the mixed-phase zone, underestimation of overall maximum echo signals throughout the profile due to lack of large precipitation particles. On the other hand, MMF V2 database show, yet not perfect, but the simulated CFAD structure has distinct three microphysics

28

645   zones and realistic distributions of solid/mixed/liquid-phase precipitation microphysics. Liiquid-

646   phase echo distributions are relatively overestimated ~5 dBZ. the improved (V2) MMF

647   simulation provides, not yet perfect, but more realistic structure of the PR.

648

649   We also found that Gaussian weighting on the GCE column alignment are critical to formulate

650   the Tb spectra for different sounder channels. Figure A1b shows the MHS-observed Tbs at 5

651   channels (89~190GHz) averaged for each instantaneous surface precipitation rate bin from

652   TRMM PR 2A25 product; the Tbs become generally colder with more intense precipitation due

653   to the effects of scattering. For light-precipitation (less than c. 2 mm h^{-1}) the 89 GHz channel

654   shows a slight increase in Tb due to emission, thereafter decrease due to scattering. The higher

655   frequencies show the 157 GHz and 190 GHz undergo the greatest scattering, followed by the

656   183±3GHz and 183±1GHz channels respectively. Importantly, at the 190GHz, 183±3GHz, and

657   183±1GHz channels, the associated thickness of the water vapor column results in the received

658   signal being dominated by the elevated mixed- and solid-phase precipitation particles above

659   lower troposphere; thus the scattering signal dominates the water vapor emission signal.

660

661   The original approach in simulating antenna-convolved Tb is to fold the 64×1 x-y 2D GCE grid

662   into artificial 9×7 x-y grid, and then applying the Gaussian weighting (mimicking microwave

663   antenna gain pattern) function to the center of 9×7 x-y grid. However, this method tends to

664   misrepresent the Tb relationship among different sounder channels from light to heavy

665   precipitation, in comparison with MHS-PR observations. Scattering magnitude for heavy rain

666   generally converged into closer magnitude among different sounder channels, and top of that,

667   scattering was significantly overestimated, and sampling of very heavy precipitation (> 15 mm hr^-

668 [1]) was completely lacked. When the Gaussian weighting function is applied directly to the 64x1

669 2D GCE grid, the sounder Tb relationship and scattering magnitude structure of all MHS

670 channels was significantly improved toward observed patterns. This result physically infers that

671 MMF-GPROF database requires realistic "structure" of cloud-precipitation-water vapor profiles.

672

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809

810 **Captions:**

811 Table 1: Sensors contributing to the Global Precipitation Measurement mission constellation

812 together with the scan type and frequencies used (those in italics are not included in this study).

813

814 Table 2: Representation of occurrence (%) of light rainfall and ratio of accumulation for

815 comparison over the United States.

816

817 Figure 1: Generic processing steps for the GPROF retrieval scheme

818

819 Figure 2: Mean rain rate per GPROF database bin for GMI (left) and MHS (right). Units for g

820 Kg^{-1} for TPW and K for Ts.

821

822 Figure 3: Ratio of rainfall accumulation by rain intensity over the United States for the AMSR2,

823 GMI, MHS and SSMIS retrievals.

824

825 Figure 4: Rain/no-rain threshold for GPROF satellite retrievals based upon comparison of

826 MRMS surface radar rainfall vs satellite rainfall estimates. A surface radar quality index of 1.0

827 (best quality) was used; period of study 6 March 2014 - 5 March 2015

828

829 Figure 5. Distribution of daily correlation coefficients (upper plot) and RMSE (lower plot) over

830 the United States based upon instantaneous precipitation retrievals from the AMSR2, GMI, MHS

831 and SSMIS sensors at the sensor resolution. The clear outlined bars (upper plot) and dashed line

832 (lower plot) represent the performance of the SSMIS retrievals at 15 x 15 km resolution rather

833   than the 44.2 x 27.5 km retrieval resolution. Only days with an occurrence of precipitation > 1%

834   are included in the comparison.

835

836   Figure 6. Distribution of daily correlation coefficients (upper plot) and RMSE (lower plot) over

837   Western Europe based upon instantaneous precipitation retrievals from the AMSR2, GMI, MHS

838   and SSMIS sensors at the sensor resolution. The clear outlined bars (upper plot) and dashed line

839   (lower plot) represent the performance of the SSMIS retrievals at 15 x 15 km resolution rather

840   than the 44.2 x 27.5 km retrieval resolution. Only days with an occurrence of precipitation > 1%

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843   Figure 7. Occurrence of daily-scale correlation coefficients for MHS retrievals over the US for

844   nadir (23-68) and edge-of-scan (1-22 and 69-90) scan positions.

845

846   Figure 8: Maps of correlation coefficients generated from instantaneous satellite/surface

847   matchups for the period 6 March 2014 through 5 March 2015 on a $1° \times 1°$ grid at the native

848   retrieval resolution of the satellite estimates (*a-d*) and for the SSMIS at 15×15 km resolution

849   (*e*).

850

851   Figure 9: Global maps of annual precipitation covering the period 6 March 2014 through 5

852   March 2015 for AMSR2, GMI, MHS and SSMIS.

853

854   Figure 10: Plots of the percent occurrence of rain intensities for instantaneous retrievals for three

855   latitudinal groups, high latitudes (90°-60°), mid-latitudes (30°-60°) and the Tropics (30°-30°),

856   for land and ocean.

857

858   Figure 11: Latitudinal profiles of mean daily rainfall (mm d^{-1}) for 6 March 2014 through 5 March

859   2015.

860

861   Figure A1: a) Contoured Frequency of Altitude Diagram (CFAD) of deep convection (echo-top

862   height > 7 km) for TRMM PR and MMF V1 and MMF V2 database; b) Tb-rainrate plot from

863   MHS-TRMM PR co-temporal/co-located data (*left*), and data simulated from MMF with

864   different Gaussian weighting with either 9x7 grid (*center*) or 64x1 (*right*) grid configuration.

865

866

867 Table 1: Sensors contributing to the Global Precipitation Measurement mission constellation

868 together with the scan type and frequencies used (those in italics are not included in this study).

Sensor	SSMIS	AMSR2	*TMI*	GMI	MHS	*SAPHIR*	*ATMS*
Satellite	DMSP-F16, F17, F18, *F19*	GCOMW1	*TRMM*	GPM	NOAA18,19, MetOp-A, B	*Megha-Tropiques*	*NPP*
Scan type	Conical	Conical	*Conical*	Conical	Cross-track	*Cross-track*	*Cross-track*
frequencies	19.35VH 22.235V 37.0VH 50.3-63.3VH 91.65VH 150H 183.31H	6.925/7.3VH 10.65VH 18.70VH 23.80VH 36.5VH 89.0VH	*10.65VH* *18.70VH* *23.80VH* *36.5VH* *89.0VH*	10.65VH 18.70VH 23.80V 36.5VH 89.0VH 165.6VH 183.31V(2)	89V 157V 183.31H (2) 190.31V	*183.31H(6)*	*23.8* *31.4* *50-3-57.3* *87-91* *164-167* *183.31(5)*
Samples/ scan	180	486	*208*	221	90	*182*	*96*
FOV* (Nadir/37 GHz)	44.2 x 27.5 km	12 x 7 km	*16 x 9 km*	14 x 8.6 km	15.88 x15.88 km	*10 x 10 km*	*16 x 16 km*
Sampling *	12.5 x 12.5 km	10 x 7 km	*13.7 x 6 km*	13.4 x 8 km	15.88 km x variable	*10 km x variable*	*16 km x variable*

869 * Figures are for along-track x cross-track dimensions.

870

871   Table 2: Summary of key characteristics of the CS-GPROF and XT-GPROF schemes

872

Feature	CS-GPROF	XT-GPROF
Database	Observation-based	MMF model-based
Surface types	15 categories	Surface-blind
Resolution	37 GHz channel*	15.88 x 15.88 km (MHS)
TPW range	0-80 g Kg^{-1}	0-95 g Kg^{-1}
Ts range	230-337 K	189-344 K
Snow retrieval	Diagnostic	Retrieval

873   *SSMIS = 44.2 x 27.5 km; AMSR2 = 12 x 7 km; GMI = 14 x 8.6 km.

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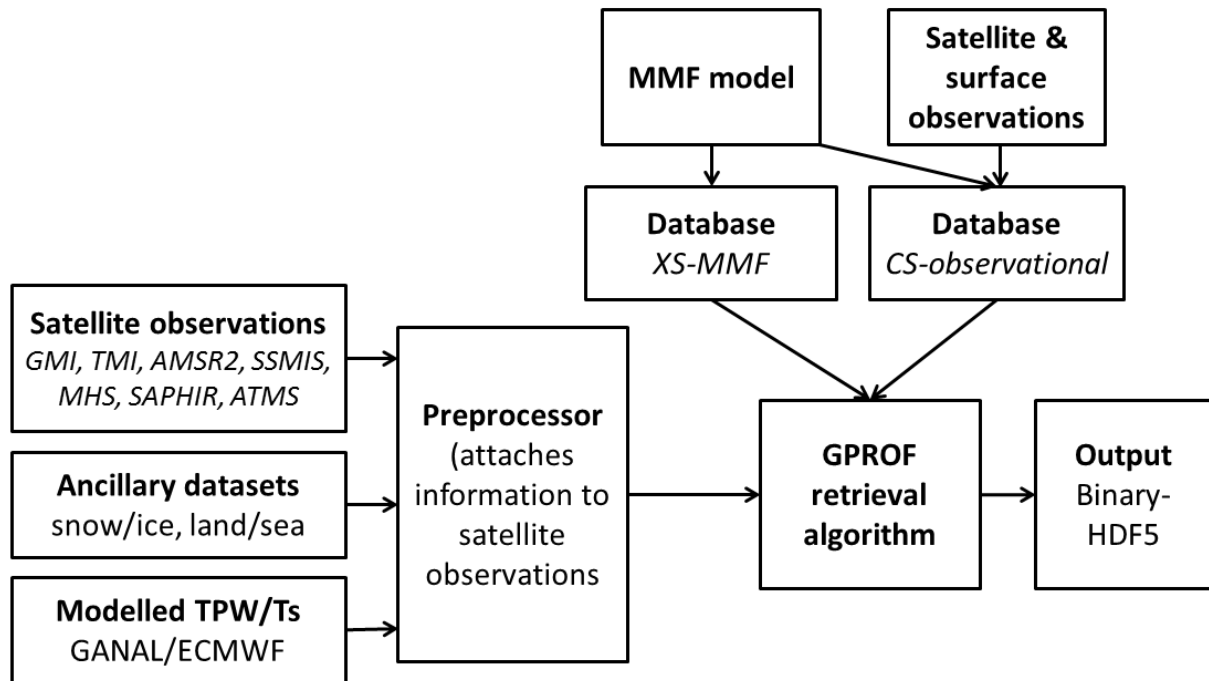
876

877   Figure 1: Generic processing steps for the GPROF retrieval scheme

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Mean rain rate per bin (mm/hr)

| | 0 | 0.25 | 0.5 | 1.0 | 2.0 | 4.0 | 8.0 | 16.0 | + |

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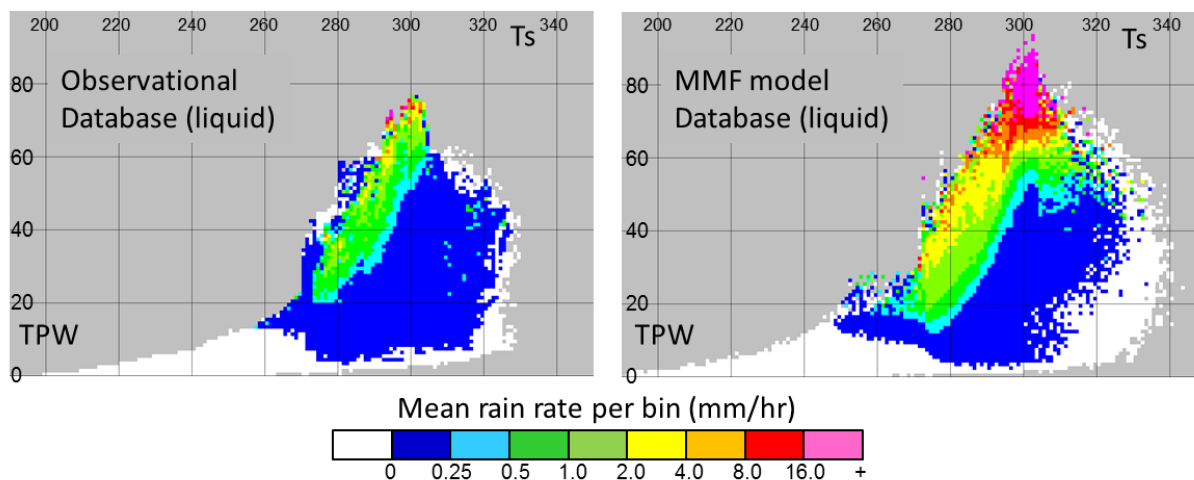
Figure 2: Mean rain rate per GPROF database bin for GMI (left) and MHS (right). Units are g

Kg^{-1} for TPW and K for Ts.

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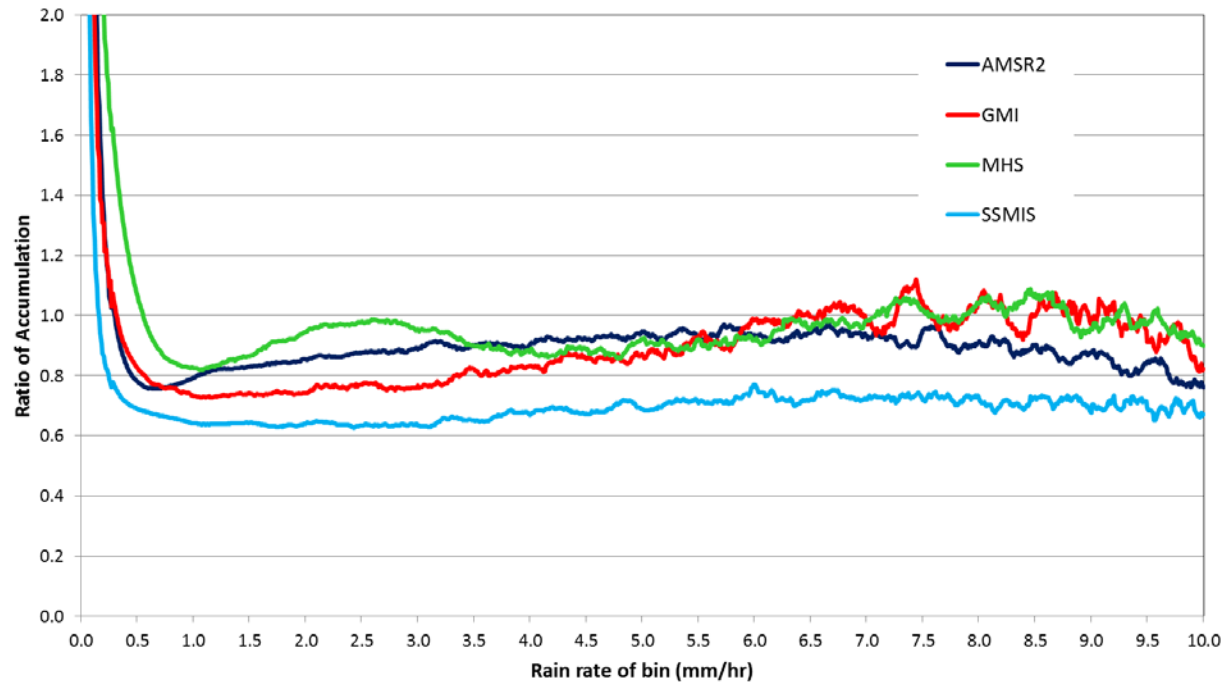
Figure 3: Ratio of rainfall accumulation by 0.01 mm h $^{-1}$ rain intensity bin over the United States for the AMSR2, GMI, MHS and SSMIS retrievals.

894

AMSR2

GMI

MHS

SSMIS

Threshold for rain/no-rain boundary (mm h^{-1})

0   0.2   0.4   0.6   0.8   1.0   1.2   1.4   1.6   1.8   2.0
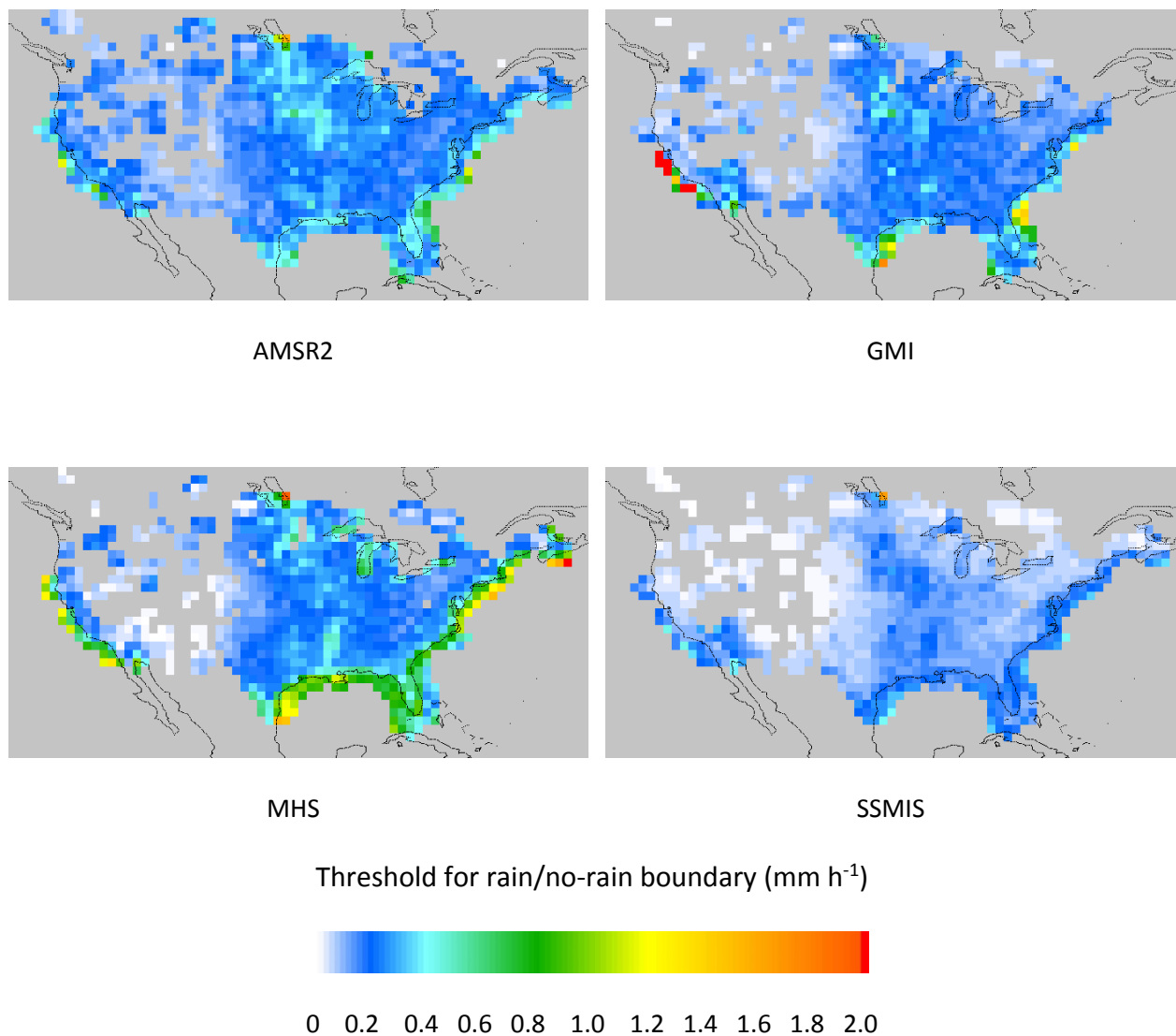
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899   Figure 4: Rain/no-rain thresholds for GPROF satellite retrievals based upon matched

900   satellite/surface radar occurrences of precipitation for the study period from 6 March 2014 to 5

901   March 2015.

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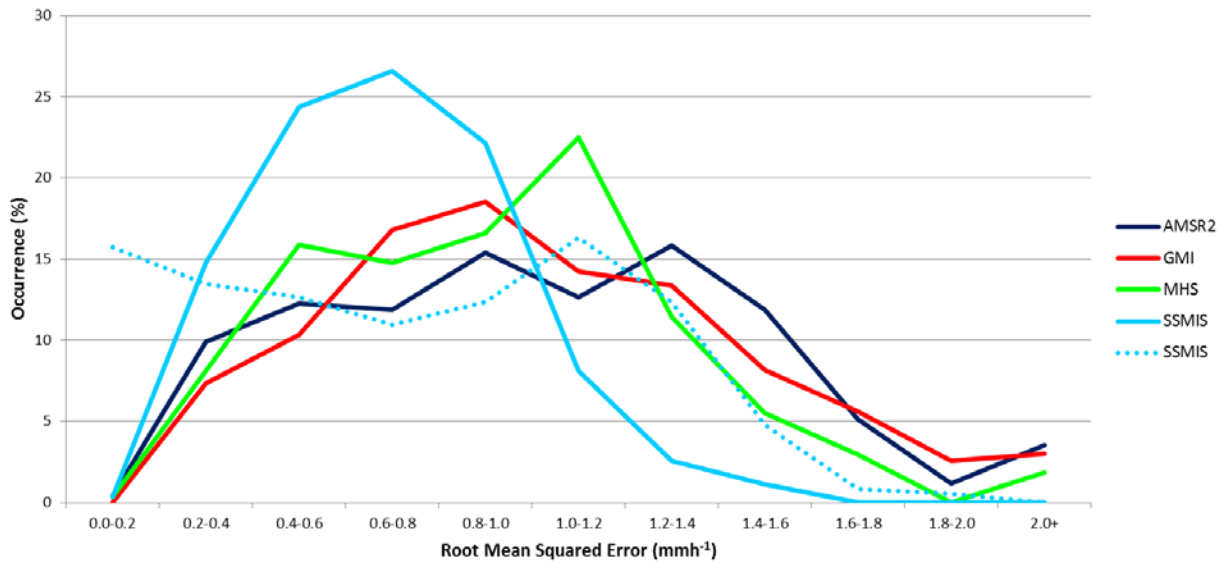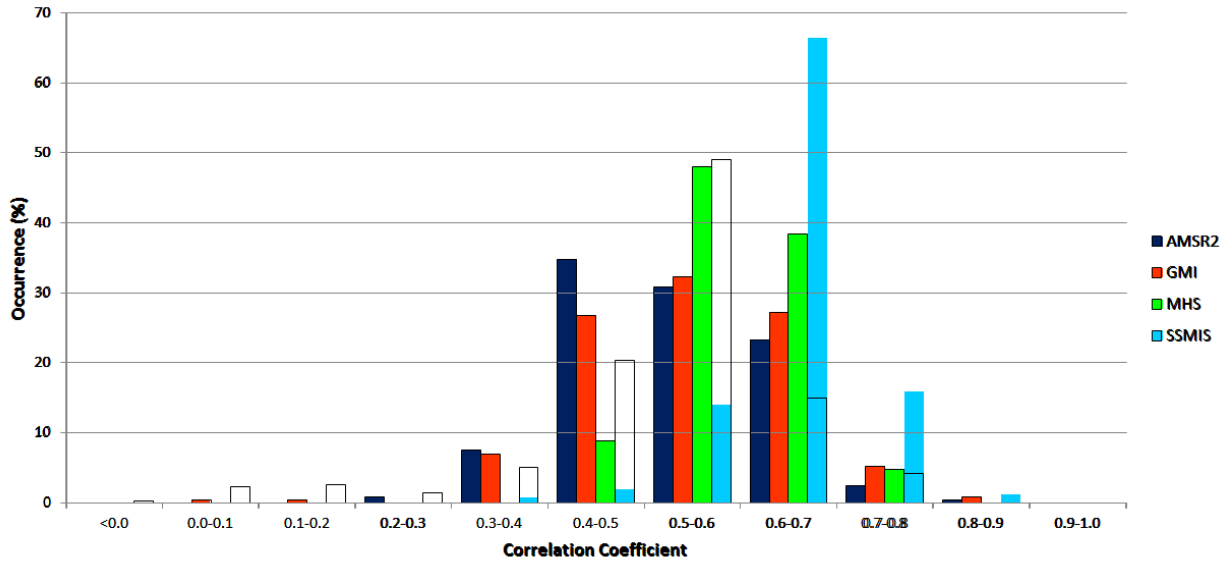
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906

Figure 5. Distribution of daily correlation coefficients (upper plot) and RMSE (lower plot) over
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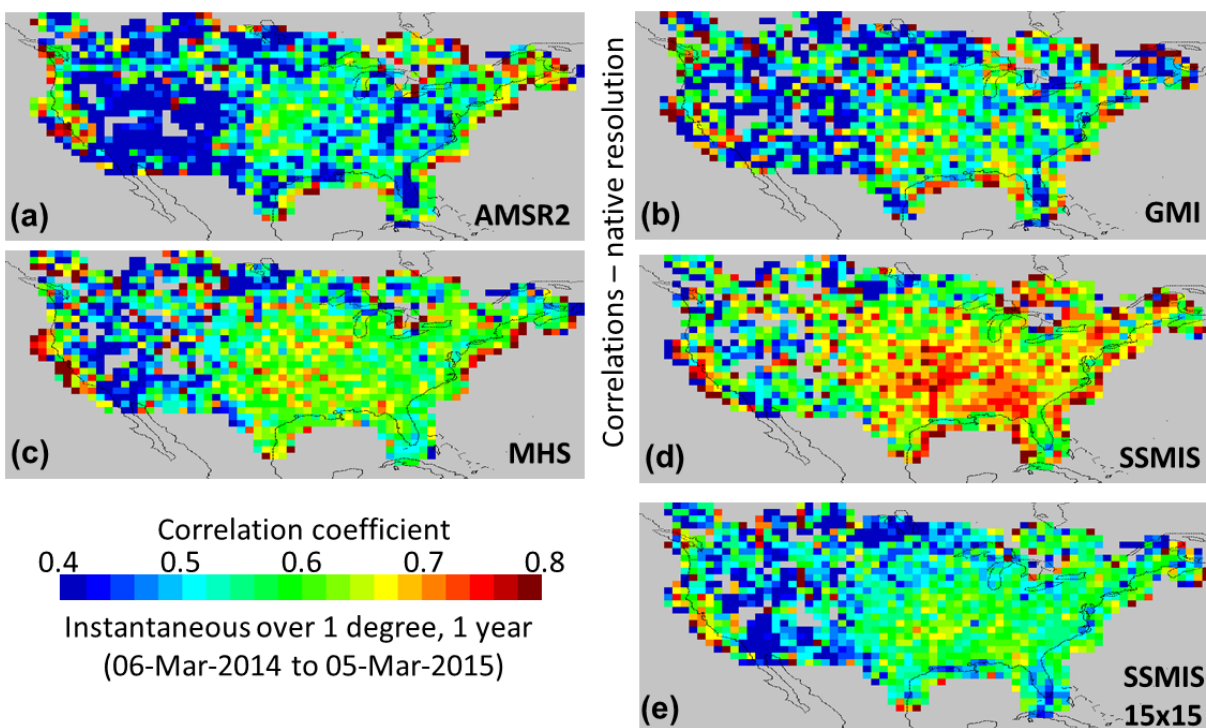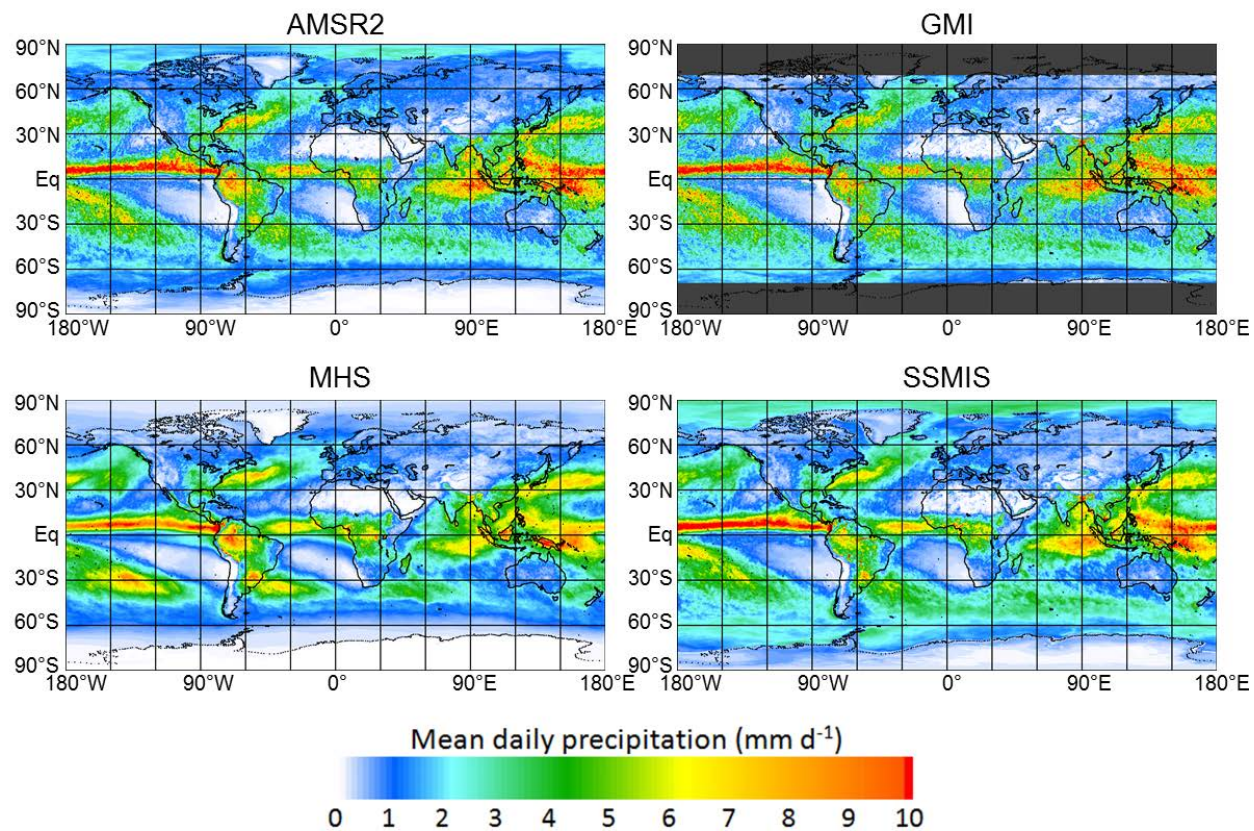are included in the comparison.

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934

Figure 9: Global maps of mean daily precipitation covering the period 6 March 2014 through 5 March 2015 for AMSR2, GMI, MHS and SSMIS.
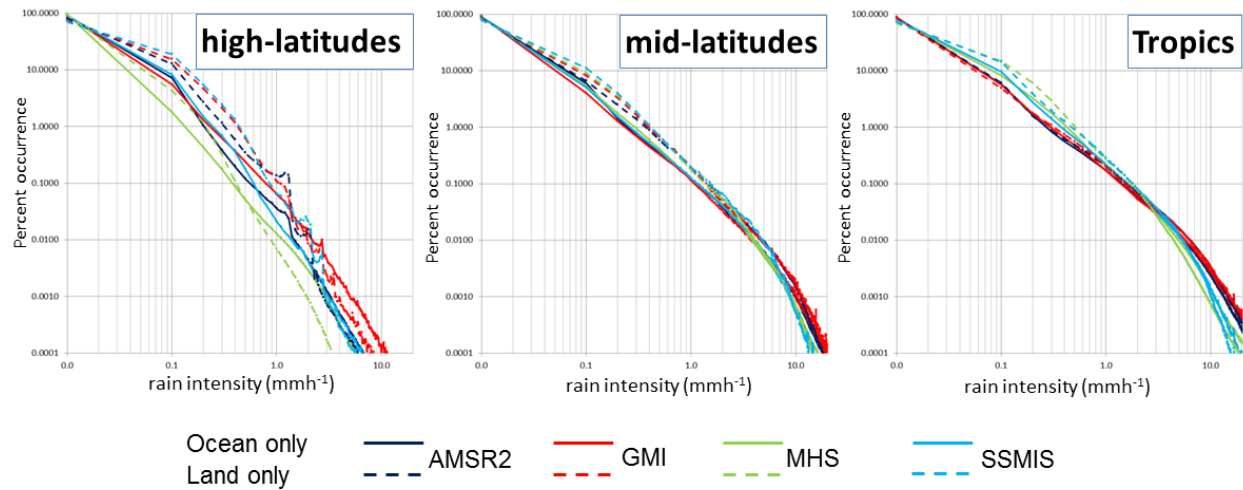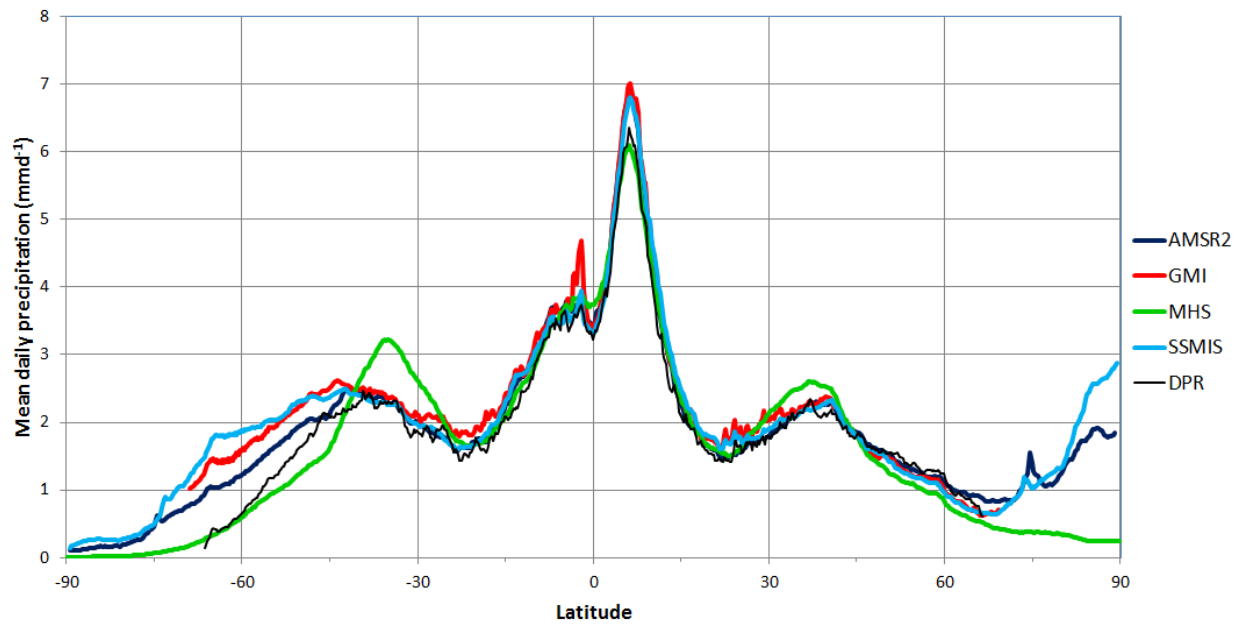
938

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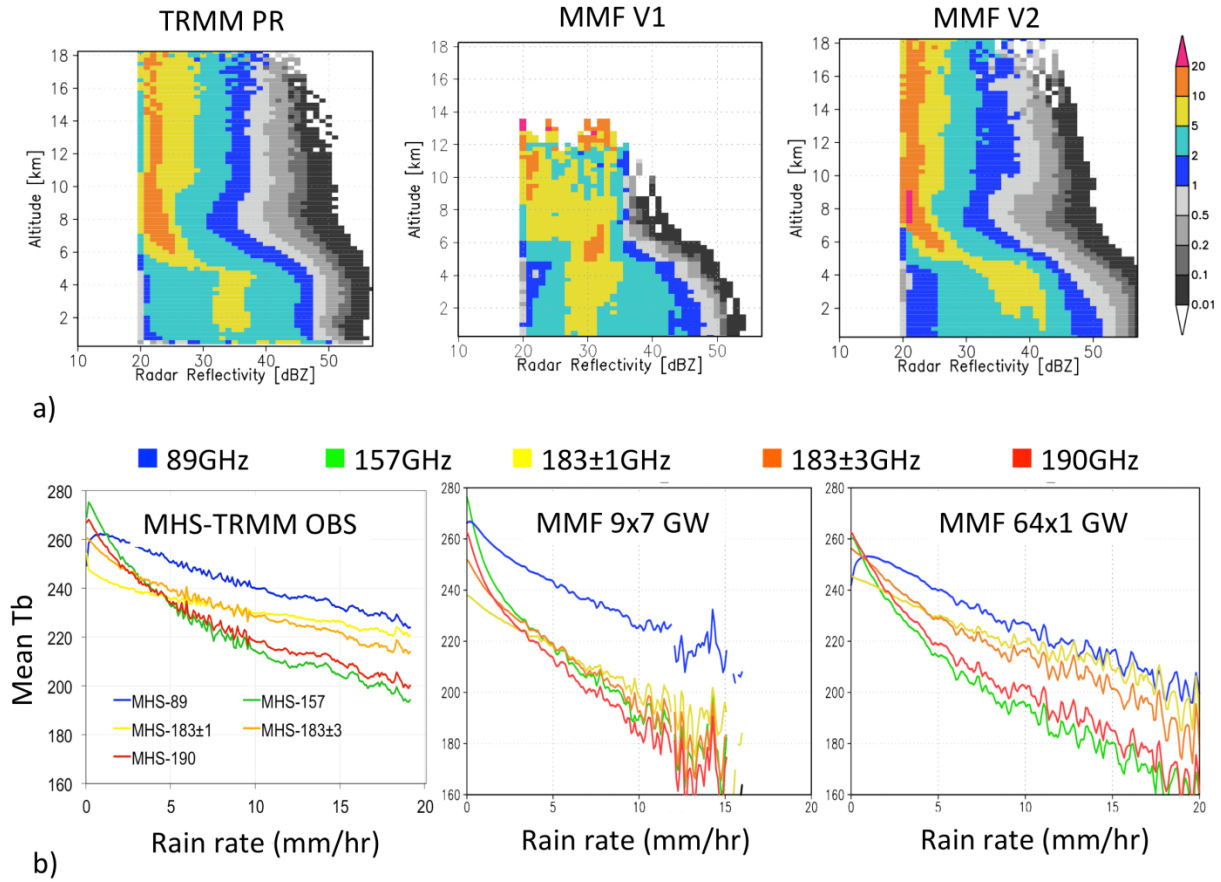
947   2015.

948

949

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